Agreement Technologies Applied to Transmission Towers Maintenance

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Abstract. In the context of Smart Cities, one of the main indispensable elements required by a city is the electric power, for which electric towers are used to distribute it. Transmission towers have electrodes which need to be reviewed on a regular basis by controlling its resistance in order to assure avoidable malfunctions not to appear. From the point of view of Smart Cities, it is possible to address this maintenance task by trying to minimize the cost of operation through the estimation of values and the reduction of the size of the population sample. To do so, the use of an intelligent-agent virtual-organization based architecture is proposed within this working environment, which by using mathematical estimation models and agreement based negotiations it is capable of maximizing the estimations, minimizing the associated cost. The proposed model is evaluated in a simulator through a real case study, which allows validating the proposed approach.

1 Introduction

One of the main areas of Information Technology (IT) focuses on the application of emerging techniques and technologies in different everyday objects. The aim is to interconnect these objects and provide them with the ability to acquire some degree of knowledge and/or intelligence, which allows obtaining new benefits and features. This new paradigm is known as the Internet of Things (IoT). One of the main fields of research and application of IoT are cities. Using IoT techniques can make them smarter, Smart Cities. Generally, Smart Cities are associated with the pursuit of benefits for citizens. These benefits may affect the society directly by offering new or improved skills; or indirectly, by using the application of IT to achieve savings.

M. Rovatsos et al. (Eds.): EUMAS 2015/AT 2015, LNAI 9571, pp. 172–187, 2016.
DOI: 10.1007/978-3-319-33509-4_15

At present, the tendency is to transform a portion of the assets of the city into intelligent entities, interconnecting them by using large-scale networks to provide data practically automatically and instantaneously. However, there are different assets of the cities that are not suitable for this transformation to IoT, either because of their nature or the cost that adapting the existing infrastructure would entail. Among these assets is the focus of this article: the Transmission Towers (TT) that transport electricity. Many are located in isolated points, where even communication through mobile technologies is limited and the cost of the required equipment to monitor and control them is too high to be included or placed on every TT. However, it is important for the TT to benefit from smart city features, which will undoubtedly result in an economic benefit.

The main benefit of IoT, in this case, is the reduction of maintenance costs, which in this type of infrastructure is complex because these costs are necessary to guarantee periodic revisions in each TT, which include measuring different parameters to ensure the security basics of the installation. In addition, such revisions are imposed by law in most developed countries [4], although the specific processes to be followed are defined in each country. The threshold value of the observable parameters in each revision is also defined, which guarantees the safety of the electric line. Undoubtedly, having to revise all TT represents a high cost, mainly due to the great distance they cover, their inaccessibility and the need for specialized equipment and personnel. However, this cost can be reduced if the number of TT to check is minimized. Obviously, there must be a high level of confidence that the TT that are not reviewed are not going to fail.

Therefore, the problem consists of predicting the TT that should be physically checked. The complexity is determined by the large amount of TT. In fact, in Spain alone there are over 42,000 km of high voltage power lines [14], many of them, supported by more than 600,000 TTs. The solution is approached from a perspective of Artificial Intelligence (AI), through the use of Virtual Organizations (VO) of intelligent agents. These autonomous entities use distributed decision making processes and incomplete information, features that cater to the proposed problem. The VO create stratified sampling to analyze the state of the lines, the samples are used to analyze the condition of similar tower over ground with similar resistivity. Taking this into consideration, the system will determine the number of TT requiring review. Agents will then have to cooperate, negotiating with each other in order to determine the final sample of TT to be reviewed. To this end, we propose a framework for negotiations based on Agreement Technologies (AT), which provides the organizational system with the capability of finding and learning solutions when the problem to solve involves reaching an agreement among the agents, with autonomy and interactions between stakeholders being the main keys. The agents incorporate a neural network to predict resistance depending on several parameters. The proposed model is evaluated in a simulation environment, which, by using real data from TTs in Spain, allows validating the results of the samples and predictions obtained.

The following section presents the problem in greater detail, as well as existing related works. In Sect. 3 the proposed multi-agent system is detailed, followed by the model of argumentation in Sect. 4. The evaluation of the system is presented in Sect. 5. Finally, Sect. 6 presents the detailed conclusions.

2 Problem Description

A TT is a structure, usually made of steel, acting as a support for aerial electric conductors which are used to transport electrical energy. Each TT has (i) an associated configuration set, defining the model, the location and other static aspects; a (ii) state, which will group a set of observable magnitudes that vary over time; and (iii) revision history, which stores the evolution of data (static and dynamic).

One of the main drawbacks and the main reason that TT must be regularly reviewed is their exposure to people, who can walk around them or even touch them. A malfunction can cause that person to suffer serious or fatal electrical shock, in addition to causing other problems with energy distribution. In order to guarantee that situations like this never happen, and for additional security reasons, the regulations of each country forces a revision of the elements involved in the distribution of electricity through high voltage power lines (in the case of Spain, the legislation is published in [4]). The revision of a TT involves a high cost when having to manage the displacement of technical equipment and specialized machinery to each TT. Furthermore, the process requires previous preparation, since the towers are active high voltage lines. Definitively, by reducing the number of supports to be measured, the value and time of completion of the operation is decreased.

Most of the problems that can arise in a TT depend on their earth leakage. To achieve a good earth leakage, each TT has a number of buried or partially buried electrodes. These electrodes are conductors that remain in contact with the ground to (i) assure the grounding of static charges or atmospheric electrical discharges; (ii) limit the flow and contact voltages in the vicinity of the support; or (iii) limit the unintentional contact voltage with higher voltage systems. Flow and contact tensions are two magnitudes with complex measurements, but they are related to the grounding voltage. Therefore, the electrodes must be properly maintained to ensure they have a resistance that is preferably low, offering sufficient capacity for current conduction.

In general, a material resistivity (!) is defined as the ratio of the magnitudes of the electric field and current density, given that a perfect conductor would have a resistivity equal to zero, while a perfect insulator would have infinite resistivity. Based on this value, it is possible to determine the ability of a conductor to act as grounded electrodes, that is, its ability to derive the current can flow from the TT.

In particular, soil resistivity depends on the materials used in the floor where the support is located, relative humidity and ambient temperature. The transmission lines should not exceed a maximum value of grounding resistance of 20 Ω, although it may vary according to the soil resistivity. It must be clear that flow and contact tensions are two magnitudes with complex measurements compared to the grounding resistance, and there there is a relationship among the three of them; therefore, the parameter with the most essential measurement is is the grounding resistance.

Wenner method [18] is used to measure resistivity, which defines the soil resistivity as:

$$\rho = Resistance \big/ K_R \tag{1}$$

This paper attempts to speed up the measurement task by estimating the most appropriate TT and designing a sample of different lines in order to validate the state of the towers. To do so, it is necessary to begin with information (locations) on a set of TTs in Spain, allowing us to know (i) the type of terrain over which it has been raised, including its (approximate) resistivity (ρ_p) and the distance to the rest of towers (d); (ii) the type of each tower, which in turn has its own coefficient of resistivity, K_R; and (iii) the line they belong to, which is important because ideally each line consists of towers of the same type; although this may not be the case with older facilities. With this information, samples are carried out to validate the state of the towers, and new configurations of towers are designed.

2.1 Transmission Tower Maintenance, Measurement and Related Works

The problem of maintenance on power lines is required mainly because of security reasons. There are different types of maintenance [2], which are presented below. First, the (i) **corrective maintenance** consists of fixing existing bugs for the system to start working correctly again. This type of maintenance can be divided, according to its required planning, into planned or unplanned maintenance. The planned corrective maintenance is a technique that ensures a reduction in costs and duration of the repair. So, classification algorithms [10] or neural networks [16, 17] have been applied to address problems of ice accumulation [9, 19] as well as the prediction of physical deterioration of machinery (generators and transformers) [13, 21]. Next, the (ii) **preventive maintenance** consists of reducing equipment failures by seeking solutions to problems before they happen. During the process, the service may be interrupted to carry out conservation work, which must be planned [1, 5]. The (iii) **predictive maintenance** arises as a complement to preventive and corrective maintenance. It consists of monitoring a number of parameters for further analysis, looking for possible anomalies. Finally, the (iv) **proactive maintenance** is a preventive maintenance strategy used to stabilize the reliability of the machinery or equipment. Within this maintenance, the work proposed in [3] stands out, where the authors manage to model the impact of proactive maintenance work theoretically. Later, thanks to the concepts of residual useful life and the models of each phase of failure, an optimal planning from the economic point of view is provided.

Although there is previous work in the maintenance of TT, there are no known jobs trying to predict the magnitudes that guarantee the safety of the line. This pioneering work makes it possible to predict and sample the number of TTs to revise through the use of intelligent agents. The system tries to predict the state of the lines by sampling the towers according to several parameters such as ground resistivity and type electrode, and other parameters such as the last revision and information taken from other towers. A VO is designed to include a specific module of ATs, whose power of argumentation is based on the use of a CBR (Case Based Reasoning), thus making it capable of learning as it is used. The VO designs the stratum and the final towers are selected through a negotiation process according to same parameters.

3 Multiagent System Description

Once the problem to be addressed has been detailed, namely, the reduction of operational costs in the maintenance of TTs, the solution is posed by an innovative approach where the set of TT to review is developed by using statistical sampling. Statistical samplings are used to estimate which resistance values are closest to a value with a maximum error and with known confidence levels, which makes it possible to avoid performing a complete analysis of a line with TT having similar features.

The problem can be addressed by a VO, which makes use of information gathered during the inspections and reviews of electrical lines. Using this information, it is possible to (i) predict the status of each TT and to (ii) determine what TT should be measured when companies have to make revisions in an area or line.

To create the model of interaction it is first necessary to analyze the motivation for potential users to use the system. Externally, there are two interest groups identified through an analysis of requirements. First, the user is the client of the application, which is used to manage the tasks related to the power lines and their maintenance. And, secondly, the provider is dedicated to updating the system information, adding new data as inspections or reviews are conducted. The VO can be framed in a dynamic but simple environment, since although new elements appear in the system, the output will always have the same format and meaning.

From this initial analysis of roles and external environment, the VO designed as part of this work can be seen in Fig. 1 and consists of the following roles:

- **User.** Represents the potential user of the system, which will use the prediction tool for optimal maintenance of power lines. Has access to the entire information repository. Finally, it is also responsible for starting a process of prediction for a set of high voltage power lines.
- **Provider.** Represents external entities that perform actual measurements in the TT; the system provides reliable information.
- **Tower.** Represents each TT and is in charge of storing each individual state. Therefore, contains information on the configuration, status, position, revision histories, etc. In addition to the agents representing the real TTs, the fictitious tower agents represent nonexistent TTs whose values have been estimated by using the final software tool.
- **Predictor.** This agent represents the predictability of the state of a TT in the system. It must have access to the repository revision histories of the TTs, as well as its information, to incorporate extra information on the estimation. The agent incorporates neural networks to predict the resistance and is used during the sample to predict the resistance of the tower.
- **Neighborhood.** Responsible for neighbor discovery of the tower agents. Able to access its information and exchange it with those agents who can know about it. The agent provides information about which TTs have the closest value to a specified distance or resistivity value.

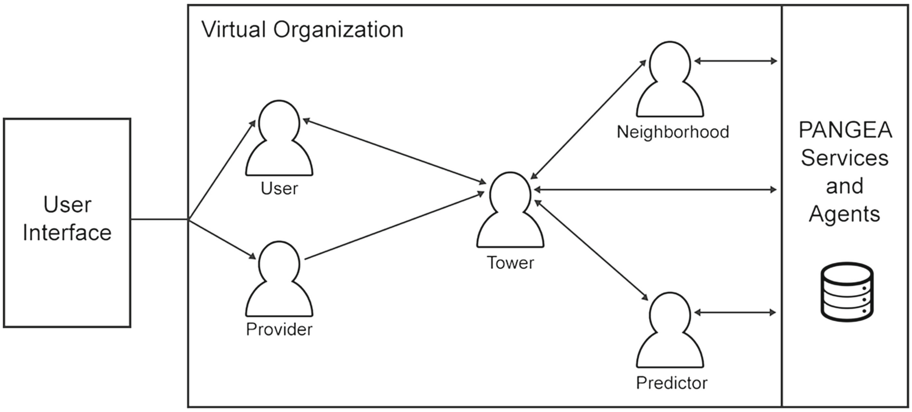

Fig. 1. MAS schema

- **Sample.** Retrieves the information of the selected towers and designs a sample over them. The agent retrieves the towers of the selected lines and designs a stratified sampling in order to reduce the number of towers reviews to carry out and perform a statistical analysis over the whole line.

In the next section the interactions between these agents are described through the model of argumentation, detailing the way they autonomously agree on the necessary revisions.

4 Argumentation Model

The proposed negotiation model is presented throughout this section. In the first subsection a required previous step is explained; in the next subsection a general overview of it is also presented; then the various designed argumentation mechanisms are presented, and finally the negotiator agent architecture is presented.

4.1 Initial Step

One of the objectives of this work is to develop a stratified sampling to carry out a statistical analysis of the lines. The samples are stratified according to the K_R and the ground resistivity in order to analyze similar towers for each stratum. Ground resistivity should not change considerably, because it depends to a greater degree on the composition of the terrain. The size of the sample is calculated for each stratum, and is defined to calculate the average resistance with a level of confidence and error. The population is divided into three groups according to the kind of electrodes and the K_R associated. Additionally, the system calculates the deciles for each group of three. The size of the sample is then calculated for every decile. The Eq. (2) define the size of the sample, the error value is defined according to Eq. (3).

$$n = \frac{z^2 \sigma_i^2 N_i}{e_i^2 (N_i - 1) + z^2 \sigma_i^2} \tag{2}$$

$$e = Max\left\{ \left(\rho_{i+1} + \rho_i\right)/2 \cdot k, \left(\rho_{i+1} - \rho_i\right) \cdot k \right\} \tag{3}$$

Where $z = 1.96$, σ is the variance, N is the population size, k is a constant defined by 0.15, ρ_i is the lower value of the resistibility in the decile i, ρ_{i+1} the upper value of the resistivity in the decile i.

For each decile we have to select the n_i elements with which the negotiation of this process is carried out. One of the desirable properties of a negotiation mechanism is flexibility, which is based on the ability of operators to refine their decision making processes and calculation of preferences during the negotiation. Since a rational agent has the ability to change its preferences if its information about the environment is updated, it seems logical to design negotiation models based on the exchange of information, which allows influencing mental attitudes and beliefs of the other agents. Therefore, an argument can be understood as a piece of meta-information that aims to make a more attractive or acceptable proposal [8]. Thus, compared to traditional cooperative models, argument-based negotiations are intended to cover this limitation.

4.2 Negotiation Description

The negotiations begin the moment the user agent requires the system to measure the sample of the TTs within a region. At that time, each TT within the territory is associated with a tower agent which checks its current Trust Percentage (TP). If TP equals 100, it means that the state of its parameters is reliable and does not require review, and therefore the agent does not participate in the negotiation. Otherwise, it does will participate by exchanging the arguments with its peers until a valid proposal is found.

During the negotiation process, all agents are connected and collaborate in pursuit of a common goal, which is to achieve the best solution based on their experiences. Thus, agents may have opposite interests:

- **Safe:** agents that promote this value will select those solutions that increase their TP.
- **Economic:** agents that promote this value will select those solutions involving the lowest revisions.
- **Neutral:** agents seeking to maximize their TP and reduce costs as much as possible, with a more relaxed posture than the others.

Each tower has a type of individual proposal (safe or economic) for the TT they represent.

Initially, to argue the individual proposal, it is necessary to obtain from the Predictor Agent the TP in the worst case of not being revised: Worst TP (WTP) (should be revised means its TP would be 100). Once this value is known, the Tower Agent determines its role in the negotiation, evaluating its history and checking two situations: (i) if the tower previously had a TP lower than the WTP (Previous TP, PTP); and (ii) consulting the Neighborhood Agent TP of its neighbors (NTP).

If there has not been a situation where $TP < WTP$, the position that the Tower Agent will adopt will be the safe one. On the other hand, if it is true that $WTP > \frac{\sum_{i=1}^{n} NTP_i}{n}$, where n is the number of neighbors, it will adopt an economic position, prioritizing the revision of its neighbors. Otherwise, its position will be neutral.

Thus, different situations may occur during the negotiation:

(a) Agents involved accept the proposal because they coincide, so the TT represented is added to the sample to be reviewed.
(b) Agents involved do not accept because more than one wishes the TT they represent to be revised.
(c) Agents involved do not accept because none wants the TT represented to be revised.
(d) The agents involved have a neutral perspective.

In situation a, because there is no agreement, the TT represented by the Tower Agent is added to the sample to review. In case b, c and d, the agents with the safe solution must negotiate to determine which TT are finally reviewed; an exchange of arguments supporting each position will use a CBR model, as detailed in subsequent sections.

4.3 Negotiation Mechanism

As previously noted, when defining a model of negotiation based on agreements in which arguments are used, it is first necessary to determine a number of mechanisms that support the negotiation process itself. The most important mechanisms are communication language and domain language.

To begin, the FIPA ACL (Foundation for Intelligent Physical Agents' Agent Communication Language) [6] is selected as the language of communication primarily because of its semantic capacity, as it includes locutions to express acceptance, rejection, proposal applications, requests, inquiries, statements, declarations, etc. Communication was made through the use of PANGEA [15, 20], which allows for a cross-platform distributed development and disengages the specific functionality of the application of basic functions, such as access to data or norms of communication between agents. For this negotiation, 4 types of locution on FIPA ACL are to be used: (i) inform: desire_to_revise (L3), desire_not_to_revise (L4), prefer_to_revise (L5), prefer_not_to_revise (L6), withdraw_dialogue (L11); (ii) propose: open_dialogue (L1); agree_to_revise (L9); (iii) accept-proposal: enter_dialogue (L2), agree_not_to_revise (L10); (iv) refuse: refuse_to_revise (L7), refuse_not_to_revise (L8).

Once the language of communication is defined, it is necessary to define a domain language, allowing the passage of meta-information separately or together with other locutions. To this end, we must define an ontology compatible with IFAP in order to carry out the decision-making process that will determine which TT are reviewed. Its class structure is defined in the Table 1.

Table 1. Negotiation ontology

Concept
AgentAction ■ Open_dialogue: area (String) ■ Agree_to_revise: proposal (Tower instance) ■ Revise: proposal (Tower instance) ■ Not_revise: proposal (Tower instance)
AgentID: agent identifier (String)
Tower: attributes (String)
Revision Requirement: constraints (String)
Revision Requirement Valuation: constraints (String): valuation (String)
Predicate
Desire_to_revise: tower (Tower instance): revision requirement (Revision Requirement instance)
Desire_not_to_revise: tower (Tower instance): revision requirement (Revision Requirement instance)
Prefer_to_revise: tower (Tower instance): revision requirement validation (Revision Requirement Validation instance)
Prefer_not_to_revise: tower (Tower instance): revision requirement validation (Revision Requirement Validation instance)
Withdraw_dialogue: area (String)

The structure is composed of two abstract classes (Concept and Predicate). The other classes are defined in the way shown in the diagram. For a better understanding, the type attributes *Attributes*, *Constraint* and *Valuation*, must be defined. First, (i) *attributes* reflects parameters that are associated with the TTs and which the Tower Agent already knows. They are needed when estimating the TP of the neighbors in the CBR. In particular, they are the model of the TT (predefined), the type of terrain on which the tower stands, the UTM (*Universal Transverse Mercator*) coordinates where the tower is located, and the number of neighbors (provided by the Neighborhood Agent). The value reflected by (ii) *constraints*, refers to its current TP and the TP it would adopt if each of its neighbors were revised. If the safe role was initially taken, it means that its WTP is the smallest one of the values sent and there are no lower values in its history. In the case of playing an economic role, it means that its WTP is larger than the smallest one of the values. Finally, (iii) *valuation* provides the level of interest of an agent in the review of each of the possibilities (it and its neighbors). In the case of adopting a safe role, the value that is associated to its current TP would take the maximum value (1), while the neighbor with the worst TP after the review would take the minimum (0). If taking an economic role, it will not be to be revised, so it will choose to take the minimum value (0) and the neighbor with the highest CP value will take the maximum value (1).

4.4 Negotiator Agent Model

Having presented a description of the model of negotiation and support mechanisms, this section will now present the structure of the negotiation agents. Figure 2 represents the structure of the Tower agent, an Argumentation-based Negotiator (ABN) which is a fundamental trait. As shown, the agents have the possibility of explicitly exchanging meta-information.

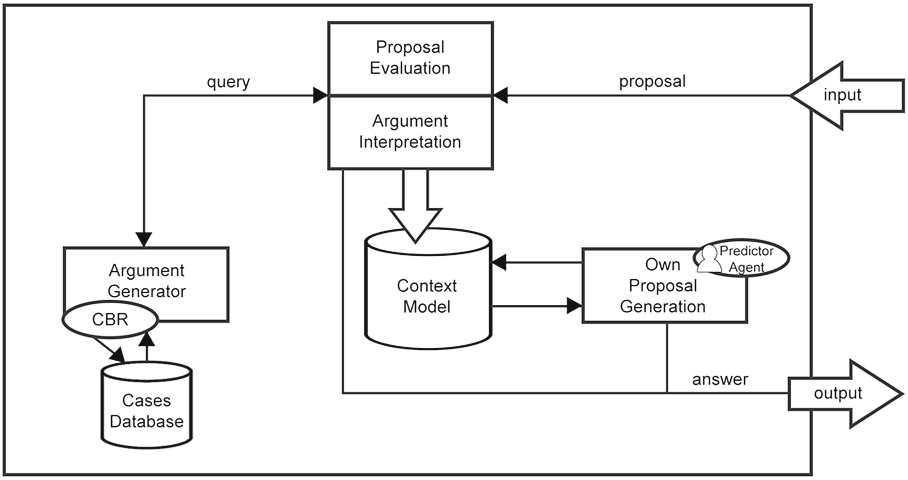

Fig. 2. ABN structure

The most important elements of the proposed ABN structure, starting with the context model, will now be presented, followed by a description of how the system is able to make predictions, and finally the argumentation model, which is where the CBR system resides.

4.4.1 Context Model

When establishing the negotiation, the TP value is important, but the arguments must also consist of other parameters such as the type of support, the type of terrain, the position of the tower and the number of neighbors. Thus, the (i) *type of support* ensures that K_r values vary in the threshold range, guaranteeing that the resistances of the electrodes are similar. Resistance grounding (ρ_p) also depends on the soil resistivity, so the terrain is another parameter whose influence is similar to that of K_r; however, it is a variable parameter that depends on environmental conditions, so it is less influential than the type of support. The (ii) *position of the tower* is important because it indicates the distance to each tower. In nearby distances of less than 5 km, and given the same type of terrain, the resistance value of the electrodes should be similar. Each Tower Agent contains information about the position of the support represented by UTM coordinates. Then, the (iii) *number of neighbors* parameter influences the negotiations, because the greater the influence over its neighbors, the higher the priority of measuring the tower.

4.4.2 Prediction

The system has two different functionalities. On the one hand the system helps to determine the model of the tower to install in a position according to the K_r and the ground resistivity, where the ground resistivity has to be calculated based on the nearest towers. On the other hand, the system has to predict the resistance for the selected towers during the sampling.

To identify the ground resistivity, a series of steps are followed. First we need to find and identify the nearest Tower Agents, for which the Delaunay triangulation method [12] is used. According to the algorithm, it is possible to generate a mesh from these points (Tower Agents) where all elements involved are vertices of one or more Delaunay triangles. Once the triangles are known, it is necessary to check the triangles to which the TT belongs, with the remaining vertices representing the TTs with less distance to the known support.

If the information corresponds to a real Tower Agent registered in the system, it is enough to obtaining the triangles where the TT represented by the Tower Agent is a vertex. If it does not belong to the system, there are two possible options: (i) the Tower Agent is within the area covered by any of the triangles of the mesh (Fig. 3); (ii) the Support Agent is located outside the area covered by the mesh. In the first situation, the nearest neighbors are the agents located in the vertexes of the triangle within which the tower is located. To determine whether a point lies on a triangle it is possible to use vector calculation or barycentric coordinate based techniques. In the second situation, it is necessary to regenerate the mesh to include the new support as part of the system. This way, the necessary links are generated and it is possible to determine the neighbors. This approach improves the accuracy of the system if the fictitious supports are consolidated as real ones.

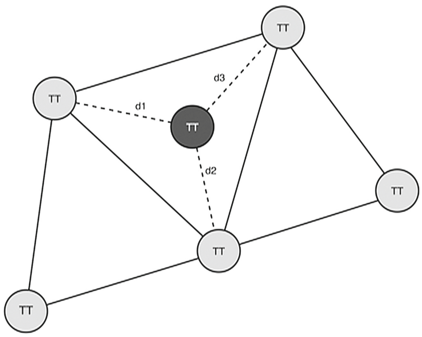

Fig. 3. TT fictitious positioning (black)

From the calculation of the mesh, the prediction is calculated as follows. First, the estimated ground resistivity $\bar{\rho}$ is calculated for a TT:

$$\bar{\rho} = \sum_{1}^{n} \rho(TT_i) * \frac{D_{max}/d_i}{\sum_1^n D_{max}/d_i} \quad (4)$$

With an estimated error of σ, where:

$$\sigma = \sqrt{\frac{1}{n}\sum_{1}^{n}(\rho_i - \bar{\rho})^2 \frac{D_{max}/d_i}{\sum_1^n D_{max}/d_i}} \tag{5}$$

In addition to predicting the resistivity, the system has to predict the resistance for new towers and for the selected towers during the sampling. To predict the resistance, a CBR model is implemented by the agents. The case is defined with (6)

$$C = \{R, \rho, K_r, h, t\} \tag{6}$$

where h is the ground humidity and t is the temperature.

The cases are divided into three groups according to the K_r and a multilayer perceptron (MLP) is trained for each subset. During the retrieve phase the agent selects the MLP based on the K_r which is used in the reuse phase to predict the resistance. The new measure is introduced in the system in the revise and retain phases. The retraining of the neural network is carried out when the number of new measures reaches a value.

The MLP networks are defined according to this structure: four input (ρ, K_r, h, t), 9 neurons in the hidden layer, 1 output with the resistance. The activation functions are sigmoid.

4.4.3 Argumentation Model

Once each of the supports has a position within the negotiations, it is necessary share them with their peers. During this process, each individual agent shares its information with its peers. If several agents have a safe position, they must negotiate with each other in order to determine the agent whose TT will finally be reviewed.

The arguments developed in the argumentation are built through a CBR. Thus, firstly the case C is established based on information provided by the opponent where, in addition to the information of each of the supports benefited from the opponent's position T_i, its current TP_i and future TP are stored (in case of revising the opponent). In other words, $TP_i^{'}$.

$$C = \left\{\, T_i = \{K_r, d, n\} \quad TP_i \quad TP_i^{'} \,\right\} \tag{7}$$

From this description of the problem, the cases that are similar in terms of K_r and position d are recovered from the cases base. Along with these cases the real $TP^{'}$, previously observed during a real revision, will be recovered, with two possible situations:

- If $TP_i \leq TP_i^{'}$, then experience shows that the opponent is right and therefore the contrary position has to be accepted.
- If $TP_i > TP_i^{'}$, then it is argued according to the recovered case or cases, where a real revision showed the error in predictions. In this case the opponent must provide new information or accept the position.

Once the negotiation is finished, those TT with the safe position are added to the revision list. Once the case has been reviewed and its parameters measured, the cases base is updated with the actual values, making it easier to deliver better results in the future.

5 Results

A tool was developed to help check the validity of the proposed system. With it, the user can ask the system for information on the TTs to be reviewed. It boasts a database of approximately 80,000 TTs with actual measurements distributed throughout Spain.

In the tool, the first step that the user must take is to define the lines or TTs that require revision, as seen in Fig. 4a. Subsequently, a detailed map of existing TTs is presented and can run the system.

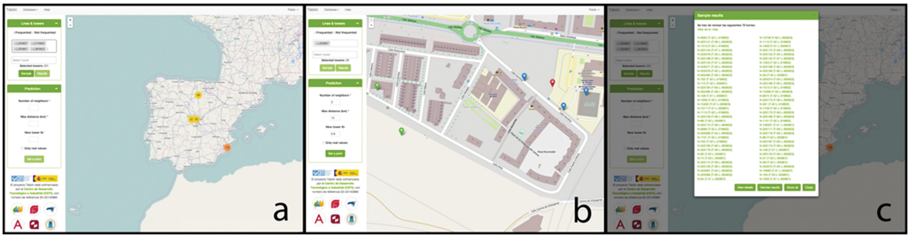

Fig. 4. Final application. (a) Line & TT filtering; (b) Fictitious TT definition; (c) TT to be reviewed

It offers added functionality such as the ability to define new measurements which are recorded in the system through the provider agent, thus becoming part of the knowledge of the agents and specially of the CBR. It also allows the definition of fictitious TTs, which are represented in the system with their respective agent and the estimated value according to the methodology explained. An example can be seen in Fig. 4b, where the red marker is the fictitious TT and the closest neighbors (three in this case) are represented with a blue marker.

The output provided to the user consists of the list of TTs that the system has resolved to propose for reviewing. The system provides different visualizations which allow consulting the TTs separately or together over the field, as shown in Fig. 4c, where a simple listing view is shown.

The accuracy of the system when predicting the resistivity of fictitious TT is mainly affected by the distance between the TTs and the truthfulness of the previously gathered data. Some of the provided existing data has been proved to be wrong because of different errors on the measurement process, so these tests have been carried out, taking into consideration the correct data gathered with this purpose. With these data, high accuracy levels were achieved as shown in Table 2.

Table 2. Accuracy percentage on the estimation according to the mean distance.

Mean distance (km)	Accuracy of the estimation (%)
~1	98.85 %
~5	97.74 %
~50	94.41 %
~300	90.15 %

These results show that the accuracy of the estimation achieved by the software tool is more efficient the lower the distance of the TT considered. This is logical, as the resistivity is a parameter directly related to the type of the terrain, so considering widely spaced TT could have a negative influence on the result even if they have a lower relevance in the algorithm. As for reducing the number of TT that should be reviewed by the technicians, the system offers a significant reduction percentage as can be seen in Table 3.

Table 3. Percentage on the estimation according to the distance with fictitious TTs.

TTs	Mean distance (km)	Proposed TTs	Reduction (%)
100	~50	27	73
200	~50	35	82.5
500	~50	64	87.2
800	~50	83	89.625
800	~300	154	80.75

The most significant reduction is achieved as a greater number of TT is preselected for review. However, a lower level reduction is achieved when TT are far apart, even when the number of TT is high. Obviously, the farther TT are located from other TT, the more different their values are. For this work, the reduction only makes sense when working on a specific area or power line, so this problem is never going to be faced.

6 Conclusions

This paper proposes a model of artificial intelligence that allows predicting and sampling the number of TT to review. With this prediction system, it is possible to reduce the maintenance cost of the power transport infrastructure. By using VO and AT it is possible to propose a system capable of reducing the number of measurements in TT, although there are factors that cannot be controlled, such as undetectable environmental changes that alter the soil resistivity.

In addition, the system presented is able to decide autonomously which TT must be reviewed. The reduction amount of the initial sample depends directly on parameters such as the distance between them, the similarity of the resistance, soil resistivity and K_r values.

In addition, sampling is useful only when correct data is available. If predicted values or previous values are significantly different to those obtained when measured, more TT are likely to be wrong, so all the initial sample should be reviewed in order to solve more errors.

Acknowledgements. TABÓN Project is a research project sponsored by the companies Iberdrola Distribución de Energía S.A., Iberdrola S.A. and ATISAE, and funded by the EEA Grants and Norway Grants (IDI-20140885).

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